# Job Training Programs for Dislocated Workers: The Positive Effects of the Workforce Innovation and Opportunity Act

by

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# Abstract

There has been a substantial amount of research the past several decades measuring the effectiveness of federally subsidized Department of Labor (DOL) programs to assist the unemployed. However, there is little to no research yet evaluating the most recent renewal of programs as defined by the Workforce Innovation and Opportunity Act (WIOA) of 2014. This paper measures the WIOA's effectiveness in helping dislocated workers who have obtained new skills, training, or education - a critically important opportunity for those who have experienced a job separation. The analysis uses probit to predict the probability of workers entering employment after training and propensity score matching on observational data to approximate an experimental setup. The matched data are then used in estimating the change in earnings conditional upon finishing training. The results are positive and statistically significant in support of the hypothesis that WIOA services help the unemployed to upgrade their skills and improve their prospects in the workforce.

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# 1 Introduction

The 2016 US presidential election was one of the most polarizing, unpredictable, and dramatic elections in recent history. Donald Trump's win over Hillary Clinton surprised many, and one issue repeatedly mentioned by both Mr. Trump and Democratic candidate Bernie Sanders was trade. Both Trump and Sanders campaigned on a protectionist trade stance that opposes trade deals such as the North American Free Trade Agreement (NAFTA) and the Trans-Pacific Partnership (TPP) because they claim that they hurt American workers. And in June of the same year, voters in Britain shocked the world by voting to exit the European Union, a result which has major implications for trade between Britain and continental Europe.

In contrast, economics has long said that governments should "let trade happen and compensate the losers". Meaning, countries are better off when they trade, and despite some job losses here and there everyone's welfare is increased by lower prices, the creation of wealth, and more consumer choices. In modern terms, "compensating the losers" means helping workers whose jobs are outsourced to adjust to new labor market realities.

Regardless of which direction this debate goes, there will be strong implications for American workers. Publicly funded job training programs have existed for decades to assist workers affected by trade directly or by distributional shifts in the economy more broadly, and there is a plethora of research evaluating them. This paper contributes to the literature and hopes to add value to the discussion by evaluating the most recent renewal of legislation that manages and funds a variety of programs to assist job seekers - the Workforce Innovation and Opportunity Act (WIOA) of 2014. The paper's hypothesis is that education and training

activities - subsidized by both the Department of Labor (DOL) and individual states and coordinated largely at the state level - can help dislocated workers reenter the workforce with wages higher than before experiencing a job separation. The research uses the most recent data to compare employment and earnings among workers who received some form of training with those who did not.

Most research looks at re-employment and earnings losses, and in some cases discusses age and previous education. Overall, they present mixed results. This paper will follow in those steps but also consider factors such as race and gender. And while some research focuses on particular US states, this research considers the universe of dislocated workers served by the WIOA. Finally, research from the past 15 years has focused on the Workforce Investment Act (WIA) of 1998. This paper's original contribution is that it focuses exclusively on the WIOA.

## 1.1 Trade Adjustment Assistance

Workers affected by foreign competition from abroad can apply for benefits generally known as Trade Adjustment Assistance (TAA). In response to jobs that are sent overseas because of increased trade and reliance on imports, the first TAA programs were enacted in 1962 and have been updated several times since then (a brief history on job training is given in the Literature Review). Today they fall under the WIOA banner making it convenient to include in this research. In this paper, "dislocated" or "displaced" workers refers to unemployed American workers in general, and TAA workers applies to those specifically affected for foreign trade. Both groups of workers are analyzed separately in this research.

## 1.2 Why Publicly-funded Training is Relevant

The question of whether and to what extent a federal agency should assist unemployed workers is a highly relevant policy question. In addition to the effects of foreign trade, the past several decades have seen recessions, the ups and downs of business cycles, the bleeding of auto manufacturing jobs that were moved to Mexico, and the Great Recession of 2008 - the biggest financial crash since the Great Depression. All these events have had a clear impact on many American workers in the form of job separation, which is why measuring the WIOA's effectiveness is important. The WIOA can ease the transition of workers from one job or career to another.

# 2 Literature Review and Theoretical Framework

All the research reviewed below is focused on the WIA of 1998 because they were carried out in the early 2000s to around 2014.

## 2.1 Brief Overview of Job Training Programs

To start with, it is important to understand the basics of the DOL programs that fund employment assistance activities because the literature discusses a variety of aspects. A 2015 report from the Congressional Research Service (CRS) provides an important history of these programs and how they operate today.

Government policy on employment assistance goes back to the New Deal, when unemployment insurance (UI) and public works projects were first introduced. The first major federal program to focus on training was the Manpower Development Training Act of 1962.

This legislation was focused on displaced workers affected by technological change - mostly low income and welfare recipients. Classroom and on-the-job training was provided.[1] Then in 1973, the Comprehensive Employment and Training Act was enacted and brought substantial changes. More authority over decision making was transferred from federal to local governments and public service employment was given a focus, although it was later removed by 1982's Job Training Partnership Act (JTPA) and then the emphasis went back to training and reemployment.[2]

The Workforce Investment Act (WIA) of 1998 replaced the JTPA and, among other sweeping changes, introduced "One-Stop" centers to provide people with a single location where they can find "training referrals, career counseling, job listings, and similar employment-related services".[3] Finally, the WIOA was passed in July 2014.

The CRS report also discusses the WIOA's Title I programs where "Workforce Development Activities" fall.[4] These activities include job search assistance, education, and training activities.[5]

## 2.2 Earnings Loss

Much has been written about the earnings loss that workers suffer after experiencing a job separation. Couch and Placzek present new research and discuss what had been done before. The collapse of Pittsburgh's steel mills in the 1970s and 80s and concomitant national recession, for example, became fodder for many research papers estimating the effect on earnings and re-employment. In their paper, the authors actually use Connecticut as a research subject and attempt to resolve a long standing debate regarding the wide

variety of earnings loss estimates; they explain how such a major event in hostile economic conditions is not generalizable to other mass layoffs during "more ordinary economic times".[6] Rather, the magnitude of earnings loss depends on factors such as the data used, whether a comparison group is used, demographic groups, and whether workers continue to work in the same industry or need to enter a new one.[7]

The authors also review the prior established findings that earnings losses in the services sector are smaller than those in manufacturing.[8] Their core finding is that overall, workers in Connecticut experienced an initial earnings loss of approximately 32% and remained at 12-15% six years later.[9] While this is an important finding, it is still limited to one US state, which is why this paper presents results based on models run at the national level. This is a different approach than building a model and defending its generalizability to other states.

## 2.3 Evaluations of the WIA

In a paper titled "Is retraining displaced workers a good investment?", the Federal Reserve Bank of Chicago considers this fundamental question and discusses the literature. The authors begin by noting three characteristics of displaced workers: 1) they have been discharged for reasons not related to their own work performance; 2) they have been permanently separated from their employers and will not likely be called back; and 3) their skills and experience were firmly rooted in a particular industry.[10]

This rough approximation is an important finding: each additional year of training increases a worker's annual earnings by about 10%; when including the overall costs of training, the real rate of return is almost 7%, adjusted for inflation. However, earnings losses can eas-

ily be 20%, so unless workers receive at least two years in a training program, they are not likely to regain those losses. Based on this, the paper finds that publicly funded training programs are important but policymakers' expectations need to be managed.[11] In reality, most training tends to be low intensity and low cost, commonly provided by two-year community colleges.[12] The paper asks the question "(s)hould we teach old dogs new tricks?" and concludes that yes, we should, because the private and social net benefits of investments in community college classes exceed the costs.[13]

The National Bureau of Economic Research conducted a study evaluating the WIA in 2013. A "selection on observed variables" identification strategy, also known as "unconfoundedness", was applied. They focus on employment and earnings impacts that are conditional on WIA participation, rather than comparing WIA participants to non-participants, because some workers might self-select into WIA. There can still be a self-selection into WIA training, though.[14] The paper's key finding is that adults who received training saw moderate positive impacts on employment and earnings but not dislocated workers.[15]

## 2.4 Evaluations of TAA Specifically

Park published a study based on workers who participated in TAA and exited the program between 2004 and 2007. The study measured whether TAA-sponsored training was a success, defined by whether or not the newly obtained skills were a direct cause of reemployment.[16] Park found that occupational skills training helped to reduce earnings loss from job separation. Workers who had limited skill sets prior to training in particular saw improved wage replacement rates.[17]

Despite some apparent success of TAA-sponsored training, there was evidence that some aspects could be improved. TAA is funded by the DOL but coordination and assistance are provided at the state level (states may contribute funding as well). It was found that training might be more fruitful if it were accompanied by career assessment and counseling because in some cases workers were trained for occupations that didn't necessarily suit them.[18] This isn't the first study to conclude this, which is why it's a good time to evaluate the WIOA in its new current form to see if these kinds of issues have been addressed.

Mathematica and Social Policy Research also conducted a performance evaluation of TAA participants from 2004 to 2011. Phone surveys were used to observe and compare workers over a four year period, comparing those who received some form of training with the comparison group who received services such as unemployment benefits, skills assessment, or counseling but not training.

The study found that TAA participants that received training had "almost entirely closed the gap in employment and earnings, and, by one measure, they had pulled slightly ahead".[19] It was also found that younger workers did better with respect to employment and earnings. Overall, the report presented a picture of mixed results. The drawback of this study, however, is that it represents only a sample of all those who participated in job assistance activities.

## 2.5 Methodological Considerations for Job Training Programs

It is worth noting the methodologies used throughout these and other articles that appear in the literature. Firstly, they are all non-experimental because while it is possible to compare workers who enter training programs with those who do not, being separated from

employment is a real life event that cannot be replicated in an experiment. Additionally, it would not be possible (or ethical) to randomly assign displaced workers into job training programs. Thus, researchers must work with real world data representing actual job losses.

Secondly, and relating to the first point, program evaluations use propensity score matching in order to create similar control and treatment groups to approximate an experimental setup. Matching also attempts to deal with the self-selection problem; workers who choose to enter training may be characteristically different from those who do not, which means a simple comparison between the two groups does not provide a meaningful insight. Matching helps to attenuate this problem by matching program participants with similar participants in the control group. The propensity score estimates the probability that the worker received the treatment.[20]

This study will use matching as well since it is considered reliable and appropriate to the circumstances.

# 3 Data and Methodology

The main dataset is derived from the Workforce Investment Act Standardized Record Data (WIASRD) file, the most recent of which - published in November 2016 - contains 3.6 million observations, each of which represents an adult, youth, or dislocated worker who received some form of job assistance service.[21] The data are prepared by states and reported to the DOL. The WIASRD covers 2013 to 2016 Q2, so workers who participated prior to 2015 were excluded because they would have been served under the WIA. The filtered data set used here captures those who participated in 2015-2016. This ensures that the observations

were served by the WIOA.

Dislocated and TAA workers are not mutually exclusive. Therefore one dataset was filtered to include only dislocated workers and another representing only TAA workers was analyzed separately.

Variables used in the analysis include demographics such as race, education, gender, low income status, and age, as well as program outcomes such as pre- and post-program earnings and employment in the quarters after finishing a program. Some additional variables were calculated such as a "finished training" variable which defines workers that finished training and those who did not receive any form of training. This is to exclude those who are currently participating in a program and have not finished yet.

Additionally, economic development across location and time was represented by GDP per capita in the worker's state during the quarter that s/he finished training. GDP per capita is a proxy measurement for average income per person and is used as a covariate in estimating the probability of reentering the workforce because that might depend on local economic conditions, not just the job training program itself. A worker in a wealthy New England state might find employment more quickly than a worker with the same skill set in a poor rural Southern state, for example.

## 3.1 Descriptive Statistics

Some descriptive statistics are given to provide an overview of the data. Table 1 shows the frequencies and percentage of totals for dislocated and TAA workers. Note that totals in the next several tables are not exactly the same because of missing values; some participants

apparently did not disclose their race, for example.

Table 1: Training status of displaced workers and TAA in dataset used for this research.

| Training Status | Dislocated Workers | | TAA | |
|---|---|---|---|---|
| | Frequency | Percent | Frequency | Percent |
| Did not receive training | 371,403 | 94.5 | 3,431 | 89.6 |
| Finished training | 21,562 | 5.5 | 397 | 10.4 |
| Total | 392,965 | 100 | 3,828 | 100 |

Table 2: Breakdown of race among displaced and TAA workers, sorted by dislocated workers' frequency.

| Training Status | Dislocated Workers | | TAA | |
|---|---|---|---|---|
| | Frequency | Percent | Frequency | Percent |
| White | 222,692 | 59.0 | 2,813 | 73.4 |
| Black | 74,140 | 19.7 | 517 | 13.5 |
| Hispanic | 55,021 | 14.6 | 274 | 7.2 |
| Asian | 11,938 | 3.2 | 143 | 3.7 |
| Multiple | 9,350 | 2.4 | 52 | 1.4 |
| Native | 3,017 | 0.8 | 25 | 0.6 |
| Pacific | 1,183 | 0.3 | 6 | 0.2 |
| Total | 377,341 | 100 | 3,830 | 100 |

Tables 2 and 3 show descriptive statistics on race and educational attainment. There is also a wide variation in program participation across states. One key takeaway from these tables is that the largest group is white with high school education. White people represent 59.0% and 73.4% of dislocated and TAA workers, respectively. Black and Hispanic people represent smaller but notably proportions. See Table 11 in the Appendix total for participation among states, including the breakdown among displaced and TAA workers.

The WIASRD contains a field for job categories such as service sector, mechanical, managerial, and administrative. It would have been informative and useful but unfortunately most observations had missing values and therefore was not used.

Table 3: Breakdown of education level among displaced and TAA workers, sorted by dislocated workers' frequency.

| Education | Dislocated Workers | | TAA | |
|---|---|---|---|---|
| | Frequency | Percent | Frequency | Percent |
| High school | 130,824 | 33.1 | 1,651 | 41.8 |
| Some college | 66,604 | 16.9 | 652 | 16.5 |
| Bachelors | 62,218 | 15.8 | 402 | 10.2 |
| Below high school | 42,717 | 10.8 | 247 | 6.3 |
| Associates | 35,693 | 9 | 498 | 12.5 |
| Beyond Bachelors | 24,614 | 6.2 | 117 | 3 |
| GED or certificate | 23,849 | 6 | 243 | 6.2 |
| Other postsecondary degree | 8,683 | 2.2 | 140 | 3.5 |
| Total | 395,202 | 100 | 3,950 | 100 |

## 3.2 Methodology

Three different models are described here. First, a probit model was used to predict a dislocated worker's employment in the first quarter (Q1) after exiting a training program. The model is given by

$$Employment = \beta_0 + \beta_1 Age + \beta_2 GDP + \beta_3 X + u,$$

where Employment is the predicted employment in Q1, Age is the worker's age, GDP is GDP per capita in the worker's state in the quarter they finished training, and X is a vector of dummy variables indicating if the worker has a Bachelors degree, a high school degree, an Associates degree, is considered low income, is hispanic, or is black.

Propensity score matching was used to approximate an experimental setup using the observational data. A logit model was used to predict each worker's propensity score and then the change in earnings conditional upon finishing training was estimated. The nearest

neighbor method and the following control variables were used: age, GDP per capita, and dummy variables indicating if a worker has a Bachelors degree, a high school degree, is considered low income, the gender, is hispanic, or is black.

Lastly, the same probit model described above for dislocated workers was also used on the TAA data set. In this case, the probability of employment in Q1 after finishing training was estimated.

# 4 Results

First, results from the probit model predicting employment for dislocated workers is presented. Then, the matching setup used in estimating the change in earnings for dislocated workers is discussed, and finally the predicted employment for TAA workers.

## 4.1 Predicted Employment of Dislocated Workers

Table 4 shows the results of the model used to predict employment of dislocated workers in Q1 and Q3 after exiting a training program. The positive values for the finished training coefficients indicate that training increases the probability of employment, although that probability decreases when going from Q1 to Q3. The values are statistically significant.

The findings allow for estimates based on actual values. The estimated probability of finding work in Q1 is shown in Table 5. A strong difference is observed between various categories of workers who completed training programs with workers who did not. As an example to illustrate the effect of training or education, a 40 year old worker who finished a training program has an estimated 88.0% probability of being employed in Q1, as opposed

Table 4: The effect of training on Q1 and Q3 employment for dislocated workers.

| Variable | $\hat{\beta}$, Q1 | $\hat{\beta}$, Q3 |
|---|---|---|
| Finished training | 0.6839$^{o}$ | 0.2245** |
| | (.018) | (.065) |
| Age | -0.0084$^{o}$ | -0.0106$^{o}$ |
| | (.000) | (.000) |
| Bachelors | 0.0561$^{o}$ | 0.0630** |
| | (.009) | (.020) |
| High school | 0.0288$^{o}$ | 0.0660$^{o}$ |
| | (.007) | (.014) |
| Associates | 0.0709$^{o}$ | 0.0870$^{o}$ |
| | (.010) | (.023) |
| Low income | -0.0993$^{o}$ | -0.1870$^{o}$ |
| | (.006) | (.014) |
| Hispanic | 0.0732$^{o}$ | 0.1299$^{o}$ |
| | (.009) | (.020) |
| Black | 0.0762$^{o}$ | 0.0386* |
| | (.008) | (.017) |
| GDP per capita | -0.0005$^{o}$ | -0.0001 |
| | (.000) | (.000) |
| Constant | 1.0898$^{o}$ | 1.1613** |
| | (.020) | (.048) |
| n | 215,246 | 48,923 |

Robust standard errors in parentheses. $*\ p < .05$, $**\ p < .01$, $^{o}\ p < .000$.

to 68.9% for the same worker who did not finish a training program. The difference between the two values is given in the "Difference" column, which is 19.1 percentage points. The average difference of these ten examples is 18.8 percentage points.

Also, a 60 year old black low income worker has an estimated 83.8% probability of finding employment in Q1, compared to 61.9% for the same worker, giving a difference of 21.9 percentage points. This is the largest difference in the examples shown, although there could be even greater example differences not shown.

Table 5: Example estimated probabilities of employment in Q1 after finishing a job training program among dislocated workers. The difference is given in percentage points.

| | Q1 employment probability (%) | | |
|---|---|---|---|
| Criteria | Training=yes | Training=no | Difference (pp) |
| Age=40 | 88.0 | 68.9 | 19.1 |
| Age=30, Black | 90.9 | 74.3 | 16.6 |
| Age=30, Low income | 87.7 | 68.3 | 19.4 |
| Age=60, Bachelors | 85.7 | 64.8 | 20.9 |
| Age=25, Hispanic | 91.5 | 75.5 | 16.0 |
| Age=50, Hispanic, high school degree | 88.4 | 69.5 | 18.9 |
| Age=60, Black, low income | 83.8 | 61.9 | 21.9 |
| age=30, Associates | 90.8 | 74.1 | 16.7 |
| Age=50, high school degree | 85.0 | 63.8 | 21.2 |
| Age=30, high school degree | 90.1 | 72.7 | 17.4 |
| Average | 88.2 | 69.4 | 18.8 |

Note that in calculating actual values, a value for GDP per capita must be used because to omit it would be akin to estimating employment in a state with zero economic growth, which is obviously unrealistic. Therefore, the median 2016 Q1 GDP per capita value among all 50 states was used, which is 539. This is the same value as that of Wisconsin. This is the reason for the very small GDP coefficient - when multiplied by a value of 500, for example, it can have a notable effect. See Table 11 in the Appendix for the full list of GDP per capita values among states.

The conclusion here is that job training programs appear to have a positive and statistically significant effect on reentering the workforce for dislocated workers.

## 4.2 Matching Procedure for Earnings Change

To start with, Table 6 shows a summary and comparison of the treatment and control groups used in the matching procedure. Of the 397,487 observations representing dislocated workers, only 34,321 reported post-program earnings and therefore could be used in the analysis. Of these, 355 were assigned to the treatment group (had participated in training) and 33,966 were in the control group (did not participate).

Table 6: Comparison between treatment and control groups used in matching analysis.

| | Control | Treatment |
|---|---|---|
| All | 33,966 | 355 |
| Matched | 355 | 355 |
| Unmatched | 33,611 | 0 |
| Discarded | 0 | 0 |

Table 7 presents the balance on the covariates. Looking at the two continuous variables, age and GDP per capita, the output shows that the balance was improved. For the total combined sample's GDP per capita variable, the difference between the mean difference in the control group and the mean difference in the treatment group was 37.8507. In the matched group, this difference was only 3.5634. The difference was less striking but still improved for age, going from a mean difference of 2.1616 to 1.5324. All variables show an improvement, given by the matched mean difference approaching zero and of the percent difference approaching 100 percent, except for the race variable Black.

Table 8 presents the results of the estimated effect of job training on a worker's wage. The coefficient of 3,900.85 represents the average difference in wages for a six month period between workers who finished training and those who did not participate in training. Based

Table 7: Balance on covariates used in matching analysis. The mean difference columns are measuring treatment minus control. A negative value means the control value is greater than the treatment value.

| Variable | Total Mean Diff | Matched Mean Diff | Percent Diff |
|---|---|---|---|
| Training | 0.0047 | 0 | 99.91 |
| Age | -2.1616 | -1.5324 | 29.11 |
| Bachelors | -0.0691 | -0.0507 | 26.64 |
| High School degree | 0.0736 | 0.0394 | 46.42 |
| Low income | 0.0255 | 0 | 100 |
| Gender | 0.1498 | 0.0366 | 75.56 |
| Hispanic | -0.0378 | -0.0282 | 25.38 |
| Black | 0.0741 | -0.1239 | -67.34 |
| GDP per capita | -37.8507 | 3.5634 | 90.59 |

on this, the average increase of a worker's yearly salary who finished a job training program is estimated to be $7,801.69.

Table 8: The effect of training on earnings. The earnings coefficient represents two quarters of wages.

| Variable | $\hat{\beta}$ | 95% Confidence Interval | |
|---|---|---|---|
| Finished training | 3,900.85* | 2,541.56 | 5,260.13 |
| | (693.52) | | |
| n | 34,321 | | |

Robust standard errors in parentheses. $* p < .000$.

The confidence interval is given as well. The results indicate that there is a 95% probability that the true average difference in wages for the six month period is between $2,541.56 and $5,260.13.

One caveat worth noting is that although the statistical significance of these results is strong and positive, as mentioned above, not all participants recorded their pre- and post-program earnings. If, for example, some workers chose to not report their earnings after

reentering employment because they were not satisfied with them, it could skew the results upwards.

## 4.3 Predicted Employment of TAA Workers

Finally, the estimated Q1 employment of TAA workers is presented. The probit model used here is the same as that used for dislocated workers except it has been applied to a smaller data set representing only TAA workers. The coefficients are given in Table 9.

Table 9: The effect of training on Q1 employment for TAA workers.

| Variable | $\hat{\beta}$ |
|---|---|
| Finished training | 0.4575** |
| | (.1500) |
| Age | -0.0224º |
| | (.0033) |
| Bachelors | 0.1206 |
| | (.1160) |
| High school | 0.0752 |
| | (.0765) |
| Associates | 0.3245** |
| | (.1194) |
| Low income | -0.1078 |
| | (.1074) |
| Hispanic | -0.0621 |
| | (.1494) |
| Black | -0.0495 |
| | (.1017) |
| GDP per capita | 0.0007** |
| | (.0003) |
| Constant | 1.2646º |
| | (.2348) |
| n | 1,687 |

Robust standard errors in parentheses. ** $p < .01$, º $p < .000$.

There are some immediate similarities between these and the dislocated workers: the finished training coefficient is a positive and statistically significant 0.4575, compared to 0.6839 for dislocated workers. This means that training still improves the estimated probability of Q1 employment for TAA workers, but the effect is somewhat less. Also, note that the constant is 1.2646, compared to 1.0898 for dislocated workers, which means that overall, TAA workers have a higher probability of finding employment than dislocated workers, with or without education or training.

Table 10: Example estimated probabilities of employment in Q1 after finishing a job training program among TAA workers. The difference is given in percentage points.

| | Q1 employment probability (%) | | |
|---|---|---|---|
| Criteria | Training=yes | Training=no | Difference (pp) |
| Age=40 | 88.8 | 77.5 | 11.3 |
| Age=30, Black | 91.7 | 82.4 | 9.3 |
| Age=30, Low income | 90.8 | 80.9 | 9.9 |
| Age=60, Bachelors | 81.2 | 66.6 | 14.6 |
| Age=25, Hispanic | 93.2 | 84.9 | 8.3 |
| Age=50, Hispanic, high school degree | 84.2 | 70.7 | 13.5 |
| Age=60, Black, low income | 72.8 | 56 | 16.8 |
| age=30, Associates | 96.1 | 90.4 | 5.7 |
| Age=50, high school degree | 85.7 | 72.8 | 12.9 |
| Age=30, high school degree | 93.5 | 85.4 | 8.1 |
| Average | 87.8 | 76.8 | 11.0 |

Example calculated values of the estimated Q1 employment of TAA workers are given in Table 10. The same example criteria are used to make for a meaningful comparison. The first striking feature of these results is that the difference between TAA workers who received training and those who did not is smaller. The average difference of the ten example calculations is 11.0 percentage points, compared with 18.8 percentage points for the dislocated

workers.

Another difference that stands out is that the average probability of employment of TAA workers with training is slightly less than for dislocated workers, but more for those who did not partake in training. While the probability of employment for dislocated workers in these examples who did not take training is 69.4%, it is 76.8% for TAA workers. This is a surprising result and implies that TAA workers are less dependent on training or education to get back into the workforce.

# 5 Conclusion

This paper has presented results in support of the hypothesis that job training programs and assistance to obtain education help dislocated workers and TAA workers reenter the workforce with higher wages. The statistically significant findings show that workers who participated in training are estimated to have a notably higher probability of entering the workforce and with higher wages compared to those who did not participate in some form of training. The positive effect of training is stronger for dislocated workers than TAA workers.

This research could be valuable to audiences as diverse as economists, economic policy makers, federal and state administrators, and labor unions. It could be relevant to both federal and state agencies that are tasked with allocating resources to help unemployed workers. As shown for both dislocated and TAA workers, older and low income workers are at a disadvantage. States might want to give special attention to workers in these groups.

The WIOA itself was a bipartisan effort, passing 95-3 in the US Senate.[22] In the summer of 2015, however, it was reported in the media and claimed by the Obama Administration

that despite showing support for legislation, Republicans were not committed to providing adequate funding.[23] In the end, 2016 funding was maintained and increased slightly for the dislocated worker programs and for training and employment services overall compared with 2015.[24] The DOL maintains optimism in its mission[25] and will likely continue to request budget increases.

The election of Donald Trump to the office of US President in November 2016 and a new Republican majority in the Senate may cast uncertainty on budget priorities. Hopefully this research can play a role in any discussion as to the future of DOL program budgets, and in particular those for dislocated and TAA workers.

One strength of this research is also a limitation – while this might be one of the first evaluations of the WIOA, it might also be too soon to fully measure its effectiveness. The results presented here are an important short term initial finding but long term evaluations are needed as well. Also, this paper set out to measure the WIOA's effectiveness, and it appears to be very positive, but this might not reflect the attributes of the WIOA alone. Other economic and labor market factors must be considered as well. A more thorough piece of research might be privy to the inner workings and bureaucratic machinery of the DOL and consider exactly how programs are implemented at the state level.

The probit and logit models used here were run at the national level. Running models at the state level were attempted as well, with mixed results. Bigger, populous states with diverse economies had good results but less so for smaller, rural states with homogeneous less skilled workforces and lower incomes. Thus, aggregate findings were presented here, but this masks the variation at the state level. GDP per capita was added to compensate for this, but there are likely other factors not taken into account. For example, some states

might be better than others at coordinating and funding the services they provide for the unemployed.

Also, some of the data were missing. As mentioned above, the job sector field had mostly missing values. It would be informative to see how employment and wages looked for workers who stayed in the same industry compared to those who had to move into a different industry. This is important because much of the previous literature focuses on manufacturing jobs up until the 1990s, but now and going forward an increasing number of jobs are in the service sector. Missing data on post-program earnings was also a noted issue in the propensity score matching analysis. A better approach would have been to impute the missing data. That is, use statistical software to fill in missing values.

Again, this analysis is looking at the short term but is only the beginning of what should be continued research - i.e., the long term. The evaluation of a job training program, especially one as large and multifaceted as the WIOA, should not end here and needs to be continued to see how worker earnings change over time. A country's workforce is dynamic and ever-changing; therefore, services geared to assist the workforce must be dynamic as well. Toward that end, this research should be continuous and ongoing.

# 6 References

# Notes


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# 7 Appendix

Table 11: Total observations among states. The Total column is from the original November 2016 WIASRD and represents all workers who received some form of WIOA service. Dis. Workers refers to dislocated workers, TAA is Trade Adjustment Assistance workers, and GDP is GDP per capita 2016 Q1. Descriptive statistics are given at the end.

| State | Total | Dis. Workers | TAA | GDP |
|---|---|---|---|---|
| Alabama | 15,745 | 477 | 39 | 426 |
| Alaska | 2,629 | 176 | 1 | 684 |
| Arizona | 21,801 | 603 | 0 | 430 |
| Arkansas | 5,714 | 242 | 0 | 421 |
| California | 228,040 | 14,557 | 56 | 639 |
| Colorado | 16,976 | 1,064 | 6 | 580 |
| Connecticut | 10,173 | 550 | 5 | 731 |
| Delaware | 3,493 | 108 | 2 | 726 |
| District of Columbia | 2,746 | 279 | 0 | 1,850 |
| Florida | 90,287 | 2,233 | 1 | 444 |
| Georgia | 32,593 | 468 | 0 | 494 |
| Hawaii | 2,211 | 112 | 0 | 567 |
| Idaho | 4,879 | 311 | 23 | 395 |
| Illinois | 46,049 | 2,521 | 22 | 611 |
| Indiana | 44,852 | 1,877 | 32 | 514 |
| Iowa | 121,468 | 17,214 | 39 | 554 |
| Kansas | 14,105 | 279 | 121 | 509 |
| Kentucky | 113,125 | 12,018 | 1,071 | 446 |
| Louisiana | 115,614 | 8,420 | 2 | 512 |
| Maine | 5,040 | 350 | 0 | 437 |
| Maryland | 15,516 | 791 | 0 | 617 |
| Massachusetts | 16,975 | 1,341 | 45 | 712 |
| Michigan | 55,205 | 1,311 | 3 | 482 |
| Minnesota | 14,395 | 831 | 0 | 611 |
| Mississippi | 25,480 | 2,688 | 2 | 364 |
| Missouri | 422,580 | 54,598 | 54 | 489 |
| Montana | 2,974 | 207 | 0 | 441 |

| | | | | |
|---|---|---|---|---|
| Nebraska | 3,712 | 565 | 2 | 600 |
| Nevada | 16,619 | 897 | 0 | 492 |
| New Hampshire | 2,969 | 341 | 1 | 563 |
| New Jersey | 31,871 | 2,648 | 32 | 647 |
| New Mexico | 7,081 | 262 | 0 | 436 |
| New York | 956,906 | 146,286 | 1,677 | 744 |
| North Carolina | 282,695 | 8,039 | 182 | 505 |
| North Dakota | 1,305 | 21 | 0 | 671 |
| Ohio | 45,511 | 2,633 | 38 | 533 |
| Oklahoma | 47,205 | 191 | 83 | 445 |
| Oregon | 316,678 | 95,681 | 0 | 544 |
| Pennsylvania | 48,058 | 2,793 | 38 | 545 |
| Rhode Island | 5,166 | 494 | 6 | 551 |
| South Carolina | 22,936 | 698 | 111 | 412 |
| South Dakota | 2,480 | 75 | 16 | 548 |
| Tennessee | 25,517 | 1,026 | 14 | 487 |
| Texas | 104,820 | 4,352 | 109 | 565 |
| Utah | 125,058 | 283 | 19 | 497 |
| Vermont | 1,979 | 91 | 4 | 498 |
| Virginia | 21,146 | 919 | 6 | 585 |
| Washington | 18,952 | 2,263 | 87 | 630 |
| West Virginia | 8,332 | 633 | 17 | 391 |
| Wisconsin | 22,535 | 620 | 16 | 539 |
| Wyoming | 2,104 | 50 | 0 | 617 |
| Total | 3,572,300 | 397,487 | 3,982 | NA |
| Mean | 70,045 | 7,794 | 108 | 563 |
| Median | 18,952 | 698 | 22 | 539 |
| Minimum | 1,305 | 21 | 1 | 364 |
| Maximum | 956,906 | 146,286 | 1,677 | 1,850 |

# 8 Curriculum Vita


## Charles D. Pedro

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**OBJECTIVE**
Software support engineer seeking to leverage quantitative and analytical skills in statistical methods, Data Visualization skills, and 11 years' Finance IT experience in order to transition into a Data Analytics role.

**RELEVANT SKILLS**
• 10+ years' professional experience using Unix, Linux and Perl; several years' experience with SQL, Python, and networking.
• Academic experience with tools such as Stata, R, Tableau, and Adobe Illustrator.
• 15+ years' professional experience with Office tools – Word, Excel, and PowerPoint.
• Experience managing projects and collaborating with teams.
• Excellent communication skills; creates documentation and conveys complex technical issues or ideas to various audiences.

**EDUCATION**
Johns Hopkins, Krieger School of Arts & Sciences, Washington, DC
MS, Government Analytics, May 2017 (expected)
Acquired Skills: Data analysis including multivariate regression and Data Visualization.

University of Sussex, Brighton, UK Graduate Diploma, Economics, July 2014

Binghamton University, Binghamton, NY BS, Electrical Engineering, May 1998

**WORK EXPERIENCE**
**Corporation for National & Community Service** (Systems Plus), Washington, DC
Tier III Support Specialist, August 2016-present
• Use Oracle SQL to resolve user and staff issues relating CNCS website and internal applications.
• Write Python scripts to automate daily maintenance tasks.

**Credit Suisse** (TSR Consulting), Morrisville, North Carolina
Level II Support Specialist, September 2014-May 2015
• Used SQL and Unix skills to re-calculate financial positions and also troubleshoot web portal issues for private banking and wealth management applications.

**Barclays Securities Japan Limited**, Tokyo, Japan
AVP, Electronic Trading Services, November 2009-February 2013
• Performed testing, configuration, maintenance, and production support of electronic trading applications that customers use to send stock market orders; worked on busy

trading floor.

**JP Morgan** (initially with Bear Stearns), New York, NY
Level III Support Engineer, April 2007-May 2009
• As main production support person, implemented daily production changes requested by business teams and worked with developers to install trading application releases.

**SunGard** (initially with GL Trade) New York, NY
Technical Account Manager, October 2005-April 2007
• Supported clients by managing installation of trading software, training, and investigation of production issues as member of Client Services team.

**Fidessa**, New York, NY
Operations Support Specialist, October 2004-October 2005
• Investigated and resolved production issues in busy, time-urgent environment to 30+ major clients using Fidessa's industry-known trading platform.

**Securities Industry Automation Corporation** (SIAC, now owned by NYSE), Brooklyn, NY Senior Console Operator, June 2001-July 2003
• Performed daily End-of-Day procedures and ran Linux scripts to shutdown applications and backup daily trading activity for National Market Systems (NMS), the customer service network that serves US stock exchanges.